Locating the Optic Disc in Retinal Images

Mira Park, Jesse S. Jin, Suhuai Luo
School of Design, Communication and IT
University of Newcastle
{mira.park@newcastle.edu.au}

Abstract

We present a method to automatically outline the optic disc in a retinal image. Our method for finding the optic disc is based on the properties of the optic disc using simple image processing algorithms which include thresholding, detection of object roundness and circle detection by Hough transformation. Our method is able to recognize the retinal images with general properties and the retinal images with variance of unusual properties since the parameters of our method can be flexibly changed by the unusual properties.

Keywords--- retinal image, optic disc, thresholding, roundness, Hough Transformation

1. Introduction

The optic nerve is one of the most important organs in human retina. The central retinal artery and central retinal vein emanate through the optic nerve, supplying the upper layers of retina with blood. The optic nerve also serves as the conduit for the flow of information from the eye to the brain [1]. The portion of the optic nerve that is visible in the retinal fundus is called the optic disc. Therefore, detection of the optic disc (OD) is an essential step in the automatic analysis of digital colour fundus images.

Fundus imaging is a common clinical procedure used to record an observation of the retina. In this paper we describe a process to automatically locate the optic disc in retinal images. Such a process could be used for automating patient screening, eye orientation tracking, image sequence registration, and automatic measurements for treatment evaluation or diagnosis.

The optic disc appears towards the left or right side of the images as a circular area, roughly one-sixth the width of the image in diameter, brighter than the surrounding area, as the convergent area of the blood vessel network. In the image of a healthy retina, all these properties (shape, colour, size, convergence) help contribute to the identification of the disc. Therefore we base our method of optic disc detection upon finding the visible properties.

2. Related work

The problem of optic disc detection has rarely received unique attention. It has been investigated as a precursor for other issues, for example as identifying a starting point for blood vessel segmentation [2,3]. It has also been investigated as a general retinal image segmentation, for instance into separate identifications of arteries, veins, the nerve, the fovea, and lesions [3,8,9]. In this paper, we only focus on the optic disc.

There are three approaches to detect the optic disc as follows:

- Geographic approach: This approach is mainly based on the information provided by the vessel structure, i.e., the fact that all retinal vessels originate from the OD. In [12], an OD tracking technique was developed for OCT (Optical Coherent Tomography) images, using a tiered scheme based on the Hough transform, eigenimage analysis and geometrical analysis based on a vasculature model. In [13], an original vessel segments fuzzy convergence algorithm was proposed to identify the position of the optic nerve image as the focal point of the blood vessels network. In this approach, the vessel information is most important than the features of OD itself and the computational complexity is very high.
- Model based approach: This approach is based on a model of the geometrical directional pattern of the retinal vascular system, and implicitly embeds the information on the OD position as the point of convergence of all vessels. Niemeijer [15] used 100 images for modelling retina vessel structure and Foracchia [14] used a representative subset of 20 images from the 81 test images. Therefore, the performance of their methods is very much depends on the models and the methods are not flexible enough to manage unexpected images.
- Image feature-based approach: This approach is based on its specific round shape and relatively high brightness, as compared to the rest of the fundus image. Kaupp [6] used split-and-merge

Proceedings of the International Conference on Computer Graphics, Imaging and Visualisation (CGIV'06)
0-7695-2606-3/06 $20.00

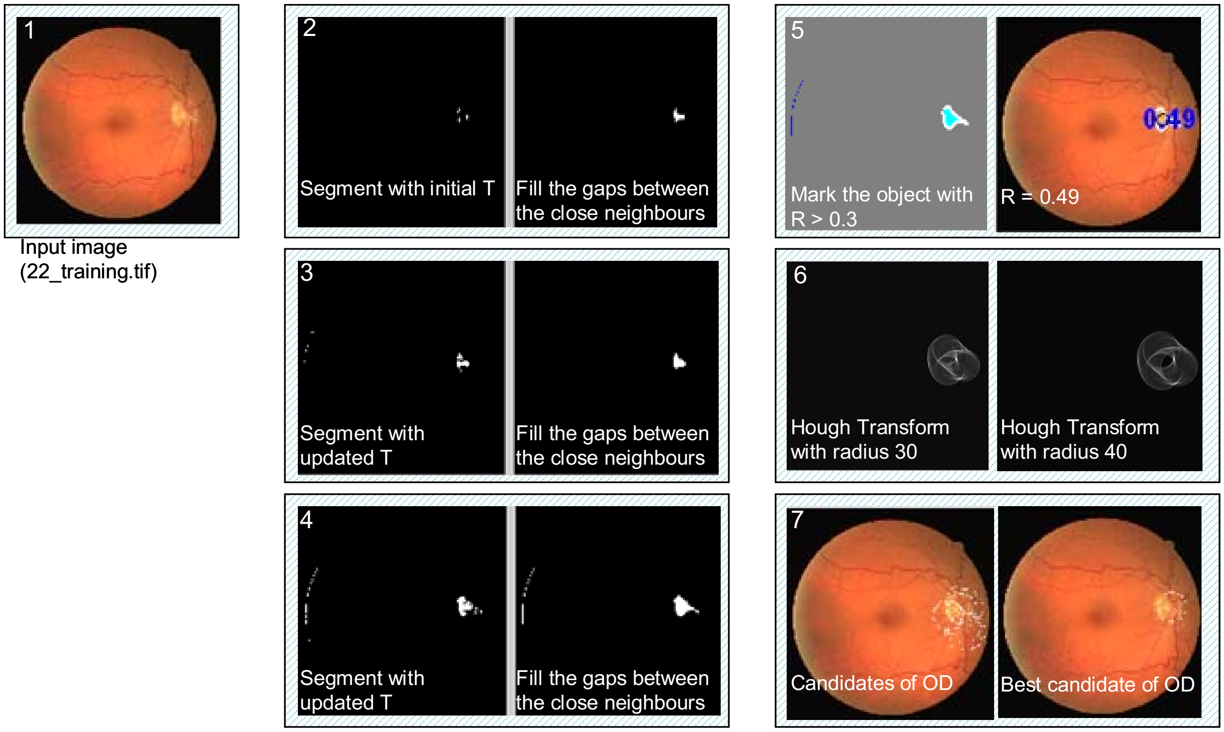

Figure 1. Detection of OD

segmentation, followed by feature based classification. The features used for classification include region intensity and shape. A similar approach was taken in [7], in which the segmentation was accomplished using matched spatial filters of bright and dark blobs. However, the optic disc segmentation was not clearly mentioned in both papers since their aims were the vessel measurement. In [10], the nerve was detected using the transform of gradient edges into a Hough space describing circle. A similar method is described in [11]. However, the image features of OD show a large variance that makes the methods brittle, particularly in the presence of retinal disease.

The characteristics of OD are still very attractive, so we propose an OD detection method which only uses the OD properties. We prevent to use vessel information for reducing the complexity and we also obtain some useful parameters from the input image for the managing of the image feature variances.

3. Methods

This algorithm identifies the optic disc as the round shape focal area with brightness. Our method first searches for several areas with a high intensity variation to localise OD and selects all rounded areas from the several areas. It then estimates the OD-contour by employing the Hough transform on the edges of the rounded areas. The Hough transform detects number OD candidates which are outlined by circles. Finally, the best candidate, which has a higher intensity, is selected as OD of the image. Our method detects the optic disc as a circle consisting of an OD centre and a radius while other methods produce only a point that can be used as the OD centre (see Figure 1).

3.1. Repeated-threshold

One of the simplest and the powerful methods to segment is through thresholding. It is useful in discriminating objects from the background in many classes of scenes. An image contains an object, which has homogeneous grey level and a background with a different grey level, usually possesses a bimodal histogram. The image can be segmented into two different regions by simple thresholding.

In its simplest form, thresholding is a point-based operation that assigns the value of 0 or 1 to each pixel of an image based on a comparison with some global threshold value T.

$$f_T(x,y) = \begin{cases} 1, & if\ f(x,y) \geq T \\ 0, & if\ f(x,y) < T \end{cases}$$

The central question in threshold segmentation is the selection of a threshold value. This is typically done interactively, based on a visual inspection of the result. Our thresholding in this paper is dynamically chosen from the input image. The threshold (T) is automatically chosen by the following process

1. Select an initial estimate for T
   The Otsu's method[18] produces optimal 1^{st} and 2^{nd} thresholding value in the range [0, 1] values and the 1^{st} thresholding value will just threshold the whole eye ball part since we do not mask the eye ball part from the background. The most optic disc can be thresholded at (1^{st} value + 2^{nd} value)/1.5, so our initial T is (1^{st} value + 2^{nd} value)/1.5
2. Segment the image using T.
   This produces two Groups: G1, pixels with value $\geq$ T and G2, with value <T
3. Take objects from G1
4. Remove all objects containing fewer than 30 pixels in G1
5. Fill the gaps between the close neighbours or fill the holes in the objects
   Only considers the graylevel pixel value, so it can leave 'gap' or 'holes' in segmented objects
6. Compute an area (Ar) and roundness (Ro) (see the next section) of each object.
7. Find at least one object which satisfy the following conditions
   (maximum_radius (100 pixels)$^2 \times \pi$) $\geq$ Ar
   and Ar $\geq$ (minimum_radius (20 pixels)$^2 \times \pi$)
   and Ro $\geq$ 0.3
8. If there is no such object, increase or decrease T
   if (maximum_radius (100 pixels)$^2 \times \pi$) < Ar
   T = T+0.05
   if Ar > (minimum_radius (20 pixels)$^2 \times \pi$)
   or Ro <0.3
   T= T-0.05
9. Repeat steps 2 to 8 until T stabilises

3.2. Roundness Measurements

Measurement of roundness requires 360° traces of the workpiece made with a turntable-type instrument or a stylus-type instrument. A least squares fit of point on the trace to a circle define the parameters of noncircularity of the workpiece. A diagram of the measurement method is shown in Figure 2.

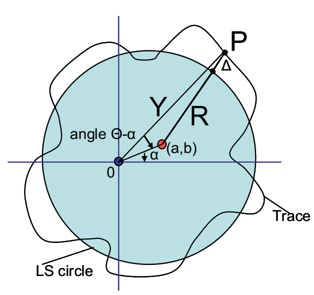

Figure 2. The trace and Y, the distance form the spindle centre to the angle.

A least squares circle fit to data at equally spaced angles gives estimates of P-R, the noncircularity, where R = radius of the circle and P=distance from the centre of the circle to the trace [4].

3.3. Circle finding using Hough Transform

Our method referenced some code in [5]. We apply the Hough transform on the detected rounded object which obtained from the previous step. We implicitly choose the radii of the optic disc candidates as 30 pixels and 40 pixels. These radii can be flexibly changed when the object is too big. For example, the distance (D) from centre to closest boundary of the object is bigger than 50 pixels, the algorithm assigns D-10, D, D+10 pixels as a radius, and if D is bigger than 100, the algorithm simply assigns 90 and 100 pixels as a radius. The algorithm filled the accumulator array corresponding to each of the above radii, where each array composed of cells for the (x,y) coordinates of the centre of the potential circle (boundary of the disc). The default size of the cells was chosen to be 4×4 pixels to function to find a circle computes the transform. For each edge pixel, it first runs through a sequence of x-values and computes the corresponding y-values for that radius. It then runs through a sequence of y-values and computes the corresponding x-values for that radius. The sequence of x-values varies from x(edge-pixel)-radius/cos(45)) to x(edge-pixel)+(radius/cos(45)). The same is true for the sequence of y-values. The two sequences are so processed because as the points reach the $x(y)$-axis, we get the same $y(x)$-values for different $x(y)$-values, for points lying on the circle corresponding to the Hough transform. This choice of sequences does not let any bias to be introduced because of choice of an x or a y sequence.

Once the Hough transform image for a particular radius is computed, it is adjusted to lie between 0 and 1 and thresholded, so as to leave only those points with high probability of being the centres. We mark a circle with a threshold value of 0.67. The resulting point-sets are then labelled with different regions. The centroids of each region are considered as centres of the detected optic discs. The output image is computed by drawing circles with these points as centres and the matched radius as the radius, and adding this to the input images.

3.4. The best candidate selection

The circles are the optic disc candidates, and we simply choose the highest average intensity since the characteristic of optic disc is brighter than other areas.

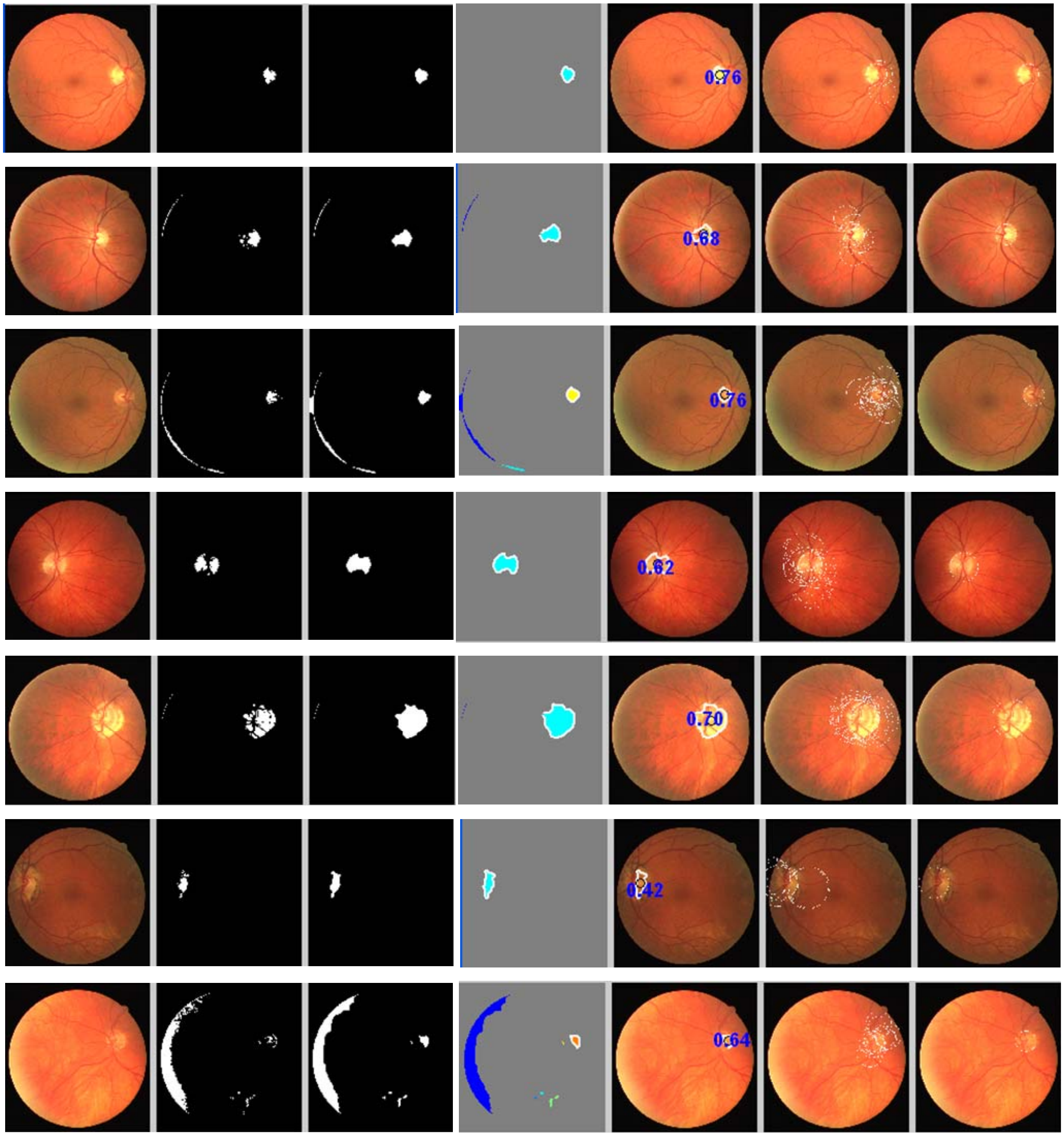

Figure 3. Examples of detected ODs

4. Results

A Matlab prototype implementing the described method was realised. An evaluation of the proposed procedure was performed using the public database (www.isi.uu.nl/Reserch/Database) [17]. The database includes 40 fundus images of the DRIVE data set (45° field of view and 584×565 pixels. The DRIVE dataset obtained from a diabetic retinopathy screening program in The Netherlands. The dataset was composed of the 20 training images and the 20 test images, but we randomly selected 5 images from the training set for training of our algorithm and we tested our algorithm with 35 test images. Our method runs took on average 4 seconds for each image on a mid-size PC (1 MHz Intel Pentium IV CPU and 1 GB RAM).

In this paper the performance of the OD detection methods was evaluated based on the determined OD location with regard to the manually segmented optic disc. The segmented optic discs consisted of a centerpoint and a radius (see Figure 3).

The success rate was 90.25%. This was a remarkable result since we only use the features of the optic disc, and a method in [16] achieved 89% of correct identification on the DRIVE dataset which is the same dataset we have used in this paper.

Conclusions

We have presented a method to automatically outline the optic disc in a retinal image. Our method for finding the optic disc is based upon simple image processing algorithms which include thresholding, detection of object roundness and circle detection by Hough transformation. Unlike model based method, our method is able to recognize the retinal images with general properties and the retinal images with variance of unusual properties since the parameters of our method can be flexibly changed by the unusual properties of input images.

The computational complexity of Hough transformation highly depends on the number of edge pixels and the number of radii to be matched. The number of edge pixels and the number of radii can be significantly reduced by the technique of detecting round objects only.

References

[1] Oyster C. The human Eye: Structure and Function, Sinauer Associates Publishing, 1999

[2] Tamura S., Okamoto Y. and Yanashima K. Zero-Crossing Interval Correction in Tracking Eye-Dundus Blood Vessels, in Pattern Recognition, 21(3):227-233, 1988

[3] Tolias Y. and Panas S. A Fuzzy Vessel Tracking Algorithm for Retinal Images Based on Fuzzy Clustering, IEEE Transaction on Medical Imaging, 17(2):263-273, 1998

[4] Reeve P. Charles, Calibration Designs for Roundness Standards, NBSIR, 79-1758:21, 1979

[5] www.cc.gatech.edu/~kwatra/computer_vision/coins.html

[6] Kaupp A., Dolemeyer A., Wilzeck R. Schlosser R. Wolf S. and Meyer-Ebrecht D., Measuring Morphological Properties of the Human Retinal Vessel System Using a Two-Stage Image Processing Approach, IEEE international Conference on Image Processing, 431-435, 1994

[7] Goldbaum M., Moezzi S., Taylor A., and Chatterjee S., Boyd J., Hunter E. and Jain R., Automated Diagnosis and Image Understanding with Object Extraction, Object Classfication, and Inferencing in Retinal Iamges, IEEE International Conference on Image Processing, 695-698, 1996

[8] Pinz A., Bernogger S., Datlinger P. and Kruger A., Mapping the Human Retina, IEEE Transactions on Medical Imaging, 17(4):606-619, 1998

[9] Akita K. and Kuga H., A Computer Method of Understanding Ocular Fundus Images, Pattern Recognition, 15(6):431-443

[10] Tamura S., Okamoto Y. and Yanashima K., Zero-Crossing Internal Correction in Tracing Eye-Fundus Blood Vessels, Pattern Recognition, 21(3):227-233, 1988

[11] Barrett S., Naess E. and Molvik T., Employing the Hough Transform to locate the optic disk, Biomedical Sciences Instrumentation, 37:81-86, 2001

[12] Koozekanani D., Boyer C., Roberts C. and Katz S. Tracking the optic nerve in OCT video using dual eigenspaces and an adaptive vascular distribution model, IEEE Conf. Computer Vision and Pattern Recognition, 1:1934-1941, 2001

[13] Hoover A. and Goldbaum M., Locating the optic nerve in a netinal image using the fuzzy convergence of the blood vessels, IEEE Trans. Med. Imag, 22:951-958, 2003

[14] Foracchia M., Grisan E. and Ruggeri A., Detection of vessel caliber irregularities in color retinal fundus images by means of a matched filter response, IEEE Trains, Med. Imag, 19:203-210, 2000

[15] Niemeijer M., Ginneken B. and Haar F., Automatic detection of the optic disc, fovea and vascular arch in digital color photographs of the retina, in Proceedings of the British Machine Vision Conference, 109-118, 2005

[16] Niemeijer M., Ginneken B., Loog M. and Abramoff M.D., Comparative study of retinal vessel segmentation methods on a new publicly available database, SPIE Medical Imaging, 5370:648-656, 2004

[17] http://www.isi.uu.nl/Research/Databases/DRIVE/ DRIVE: Digital Retinal Images for Vessel Extraction

[18] Otsu, N., "A Threshold Selection Method from Gray-Level Histograms," IEEE Transactions on Systems, Man, and Cybernetics, Vol. 9, No. 1, 1979, pp. 62-66

0-7695-2606-3/06 $20.00 © 2006 IEEE